Evaluation of Product Usability using Improved FP-Growth Frequent Itemset Algorithm and DSLC – FOA Algorithm for Alleviating Feature Fatigue

Midhunchakkaravarthy[1], Divya[2], Debnath Bhattacharyya[3] and Tai-hoon Kim[4*]

[1]*Faculty of Computer Science and Multimedia,*
Lincoln University College, Malaysia
[2]*Center of Postgraduate Studies, Lincoln University College, Malaysia*
[3]*Dept. of Computer Science and Engineering,*
Vignan's Institute of Information Technology, Visakhapatnam, India
[4]*Dept. of Convergence Security, Sunghin Women's University, Seoul, South Korea*
[1]*midhun.research@gmail.com,* [2]*divya.phd.research@gmail.com,*
[3]*debnathb@gmail.com,* [4*]*taihoonn@daum.net*

Abstract

The development of E-commerce websites in recent years has attracted more people to buy products and services online. The development has also hooked the organizations to involve in online business processing for better growth. Generally, customers are intended to buy products with more features. Based on this traditional customer purchase behavior, the manufacturers design their product with the maximum number of features. Later, customers after using the products may get dissatisfied due to product features that are not suitable for the product. As this customer dissatisfaction is because of unwanted product features, it is termed as Feature Fatigue of a product. Nowadays customers post their opinions on E-commerce websites as reviews. For the organizations, it is the most important aspect to consider online reviews posted by existing customers. Hence those reviews may also reflect Feature Fatigue (FF) which affects the reputation and organization's growth. To solve this feature fatigue problem a novel method linear Diminishing Step and Logistic Chaos with Fruit fly Optimization Algorithm (DSLC –FOA) based Association Rule Mining (DFARM) is proposed in this paper to evaluate the product usability. In DFARM, improved Frequent Pattern – Growth (FP-Growth) Frequent Itemset algorithm has been improvised and incorporated using DSLC-FOA algorithm to evaluate the product usability. Further feature fatigue analysis is applied using Genetic Algorithm to obtain the FF Degree through usability evaluation and capability evaluation of each feature.

Keywords: Product usability, Capability evaluation, Feature Fatigue, DSLC-FOA, FP-Growth

1. Introduction

The customers in recent years highly depend on online purchasing where the organizations are competitive in online business platform [1]. The organizations face many challenges to compete with others in the online business. In which most important challenge is to understand customers purchase behavior [2]. This understanding can be determined through analyzing the customer reviews based on their preferences [3]. Thus, customers' reviews are an important aspect of analyzing customers purchase behavior and

provide support to make decisions in product designing. The growth of online business transactions and interest shown by the customers to purchase products online are phenomenal [4].

This involvement of online technology in the business world tends the leading manufacturers to concentrate more on online customers. The customers prefer to buy the products with more features during purchase [5]. In traditional business processes, it is imposed to add more features for increasing the Product Capability (PC), product quality and the profit [6]. But, due to the addition of many features in the products, customers are affected by high complexity in using of unwanted features of a product [7]. This results in dissatisfaction of customers on the product feature usability, which is called as Feature Fatigue (FF) [8].

The product feature usability problem will widely spread among the customers through Word Of Mouth (WOM) which affects the growth of manufacturers [9]. Hence it is highly important to remove the Feature Fatigue of a product. The major concerned areas of this research work are online product reviews, product usability, and Feature Fatigue, which are discussed briefly in the following sub-sections.

1.1. Online Product Reviews

These days most people are interested in using e-commerce websites to purchase the products [10]. This situation is because of proliferating e-commerce websites provided to the customers for buying the products [11]. The concept of online shopping varies from customary shopping in several behaviors. The important behavior is customers are not provided with the chances to see, realize and verify the products as they can do with customary shopping. The customers can only depend on the information provided by the manufacturers in online. To overcome this limitation the manufacturers provided the facility to the customers to share their experiences on the product usability in online with other customers [12]. The range of increasing online customers increases the habit of posting reviews about products online [4]. The reviews posted by customers in e-commerce websites about the products are like WOM [8]. Part of customers considers the reviews of existing customers as an important key in deciding to purchase the products [13]. In general, while posting the reviews customers expresses their impact on the features of a product they purchased earlier. These reviews clear out customers' opinions about the product features. Thus, it helps manufacturers to know the market opinion about their product [14].

1.2. Product Usability

At the time of purchase, the customers usually compare the usability of the product to make a purchase decision. Usability is the tool identify product acceptance of the customers. Also, it is the important customer requirement of a product [15] and considered as a tool to succeed in the market [16]. Usability analysis is the requirement analysis, which helps in identifying, analyzing, and satisfies customers' requirements and provides the opinions of the product to design and modify. The products with high usability provide high customer satisfaction; hence to lead in the market the manufacturers provide the products with high feature usability to satisfy the customers' requirements [16]. The product feature usability evaluation is performed to identify customer and product relationship based on usage. Thus, product feature usability evaluation is considered as an important way to improve product development based on customer requirements [8].

1.3. Feature Fatigue

The earlier researches show that by increasing the number of features to a product, the product capability can be increased through which product quality is also improved and final results in improved profit [12]. Even then adding more features to a product may

create difficulty for the customer to use the product. This difficulty will result in dissatisfaction of a customer on a product, which is known as Feature Fatigue (FF) [16]. FF is an occurrence where customers tend to buy products with a maximum number of features at the time of purchasing before use, product dissatisfied after use due to unwanted features in the product. FF creates negative WOM, which can spread widely and will bring down the product and manufacturer reputation in the market. This will result in a loss of longterm customers of the organization [17]. The best method to remove FF is to minimize or remove unwanted features in a product and design the product with optimal features set of balancing Product Capability (PC) and Product Usability (PU).

2. Literature Review

The existing methods used to analyze online reviews, evaluate product feature usability and analyze feature fatigue are listed in the following sections.

2.1. Online Customer Reviews and Related Theories

The online reviews posted by the customers provide the information about products and their features availed by the organizations [18]. The count of customer reviews and customer ratings upon the product identifies the accurate aspect to be considered in increasing the purchase behavior [3]. The various existing approaches and models applied to analyze the online reviews posted by customers about the product and features upon usability are discussed in detail below.

Chong *et al.*, [2] proposed a big data architecture for analyzing web data, where asynchronous input and output are used to request, extract and preprocess the data in real-time. The big data architecture is employed for analyzing the sentiment through applying Application Programmer Interface (API) text processing with an online classifier to process the collected reviews. Those collected reviews are then labeled with semantic values and finally, three-layered neural network modeling is applied to examine the predictors of online product sales. As a result, the online reviews are confirmed as an important predictor in online sales of a product.

Chen *et al.*, [18] proposed three review helpfulness hypotheses, based on illustrative inferences in three aspects as reviewers, review characteristics, and several review votes. And the reasonability is verified with real-time review data. This discovers the relationship between helpfulness of a review with other aspects of online product sales. The result obtained based on the three hypotheses are, the reviews from customers, the high reviews valances and reviews with maximum votes provide helpfulness which helps in different aspects of online product sales.

Zimmermann *et al.*, [19] proposed a framework, OPINSTREAM to identify and classify the product features based on public reviews on different products. The framework includes the processing of stream clustering, product feature extraction based on clusters, sentiment learning of each cluster. In this work, the OPINSTREAM is applied through an adoption mechanism incorporated with semi-supervised classification method for evaluation. The result determined was with better quality and time consumption upon execution.

Asghar *et al.*, [20] proposed a rule-based approach to identify the classification of opinions from online reviews. In this approach, the product reviews are extracted based on Lexicon opinion mining. Those reviews are then classified as subjective and objective reviews. Then polarity values of subjective reviews are evaluated from the classification. Upon experimentation of this approach, the result achieved was 86% accurate on feedback 85% on reviews.

Lizhen *et al.*, [21] proposed a vector model based on product features for effective analysis of sentiment orientation in review sentences. The model is applied with a novel feature weighting algorithm, High Adverb of Degree Count (HADC) for classifying the

sentiment orientation based on related information in the review sentences. The HADC weighting algorithm resulted in classifying reviews at 87.5% in the least case and achieved 91% accuracy in the best case.

2.2. Various Existing Methods of Product Usability Evaluation

Razza *et al.*, [22] proposed Multiple Linear Regression (MLR) to identify the correlation between product features and usability. As a result, the Correlation, a matrix is constructed by setting up values for high correlation and moderate correlation as 0.8 and 0.4 respectively. Upon the analysis carried out on disposable razors, it was found that there was no strong correlation between the product feature and usability. For effective product feature usability evaluation, statistical methods such as genetic algorithm, neural network, and fuzzy logic are suggested by the authors for further process.

Wu *et al.*, [1] proposed a web mining approach for product usability evaluation and Feature Fatigue analysis. The customers' reviews are collected from the web using web crawler and preprocessed into review sentences and product feature extraction is performed to form a synonym dictionary. For evaluating the product usability rules are generated by applying FP- growth, frequent itemset algorithm and pruned for reducing the rules. Usability scores and Capability scores are calculated based on the evaluation. In the FF analysis, FF Degree is calculated for each product feature. The result obtained is three features out of seven features were identified with negative FF degree values. This helps the product designers to remove the features with negative values to remove FF of a product.

Wu *et al.*, [23] applied an approach based on review mining for product usability analysis. The analysis is performed by using opinion mining technology for word segmentation and word frequency to convert unstructured review information into structured feature reviews and to identify the semantic orientation of the reviews. In usability evaluation, Kaiser-Meyer-Olkin (KMO) test and Bartlett Test of Sphericity (BTS) is processed for factor analysis to extract feature reviews related to usability. The sentiment scores of product features are calculated to identify the usability and the performance of the product thus helps the manufacturers in developing the least scored product feature.

Long *et al.*, [14] applied web semantic mining method on Chinese customer reviews to analyze product feature usability. The analysis is performed in three steps as a collection of related review words, developing product usability and information system and product feature usability evaluation. In the first step, the word similarity is calculated and related words are identified. In step 2, online reviews are collected using web crawler and analyzed with review words identified in step1 for product usability evaluation. And in step 3, by collecting the Pros and Cons of each feature of the product from the customers, is evaluated. The method was feasible and effective in evaluating total usability score of a product.

Liping *et al.*, [24] proposed Fuzzy Analytic Hierarchy Process (FAHP) to evaluate product usability. In this research work, customers' subjective experience is considered as an important index to identify and evaluate. The usability is derived into three categories as apparent, perceived and performing usability. In FAHP model, fuzzy evaluation matrix is constructed through membership degrees and the values of apparent usability, perceived usability, and performing usability are identified and rated through mean and standard deviation. The model helps to evaluate product usability quantitatively and identifies the product usability problems effectively.

2.3. Different Existing Methods Applied for Feature Fatigue Analysis

Chai *et al.*, [25] proposed Norton Bass Model to identify optimal feature combination to increase the Customer Equity (CE). Initially, Norton Bass Model (NBA) is evaluated

to identify the effects of WOM based on customers' purchase behavior. In the customer transition model, WOM is analyzed based on customers' purchase behavior. And using the customers' purchase analysis, CE is evaluated. Finally, Combinatorial Optimization Problem (COP) is evaluated between capability and usability by applying a genetic algorithm. CE identified is applied as a fitness function for GA evaluation in identifying the optimal feature combination set. This approach increased the CE to about 18% which helps the manufacturers in improving CE to the product with more features.

Wu *et al.*, [6] in another work proposed an approach based on Kano's model to remove FF. The work initially focuses on identifying the problems in Customer Requirements (CRs) using Continuous Fuzzy Kano's Model (CFKM) to reduce the unwanted features of the product. Then product capability, product usability and FF Index (FFI) are processed in FF analysis. The features with FFI values greater than the threshold value $FFI \geq (\varphi) = 0.10$ is incorporated into the product. Among 11 features only five features are identified with greater values to be added to the product. This helps the product designed to analyze and integrate only the needed features into the product to improve the product quality and as to remove FF.

Wu *et al.*, [20] proposed Bass model for predicting and alleviating feature fatigue of a product. The model is integrated with WOM effects, product usability and capability evaluations identify the impact of product features to be added in product designing. The Customer Equity (CE) is evaluated through the integrated model and analyzed to attain maximum CE of a product. The model proposed in this work maximizes the CE for long-term profits as shown in the result of the case study, experimentation the manufacturers gained the maximum CE of $340.91. Thus, achieves focus of the work that predicts FF which can support the manufacturers in deciding on adding features to the product and maximizes the CE.

Wu *et al.*, [26] in another work the Bass model is proposed to perform Feature Fatigue (FF) analysis on Customer Equity (CE). The based model analysis is performed based on WOM effects upon usability and capability to identify CE with the product. FF Degree (FFD) is evaluated by identifying the usability score and capability score of each potential feature of the product and ranked. The results achieved in this work helps the manufacturers to consider the values of FF in obtaining CE and provides support in making decisions on alleviating FF from the product.

Wu *et al.*, [27] in another work proposed Susceptible-Infected-Recovered (SIR) epidemic model with a genetic algorithm to identify optimal feature combination for increasing the Customer Equity (CE). Initially, the SIR epidemic model is applied to illustrate WOM effects on customers' purchase behavior. And in customer transition model, WOM is analyzed based customers' purchase behavior by different feature combinations. And using the customers' purchase analysis, CE is evaluated. Finally, a genetic algorithm is applied with CE as a fitness function for evaluation, to identify the optimal feature combination set. The proposed approach increases the CE about 20%, this helps the product designers in identifying optimal feature combination set to increase CE and remove FF.

Li *et al.*, [28] proposed a Feature Fatigue Multi-Objective Genetic Algorithm (FFMOGA) to solve the problem by adding the features of a product. Initially, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is applied to identify multiple optimal solutions and Bayesian Networks (BNs) fitness function is used to calculate the capability and complexity of each product feature. Finally, features are evaluated by the genetic operators to identify multiple optimal solutions with good performance in convergence.

3. Proposed Methodology

In this paper, the DSLC - FOA with Improved FP-Growth Frequent Itemset algorithm is

used for product usability evaluation and FF degree is computed in feature fatigue analysis.

The reviews about the product and their features posted in online by the customers upon using them are collected using the web crawler tool. To provide the review sentences as input to Association rule mining process, the raw reviews collected from the web are to be preprocessed. The Natural Language Processing (NLP) with Part of Speech (POS) tagging is used for preprocessing. To develop synonym dictionary after preprocessing, Latent Dirichlet Allocation (LDA) and Synonym Lexicon methods are used. The filtering rules are generated to process the extracted features to identify the product features. To evaluate product usability and analyze feature fatigue, DSLC - FOA Algorithm based Association Rule Mining (DFARM) is proposed.

In DFARM, improved FP-Growth frequent Itemset algorithm of Association rule mining approach is improvised to generate a minimum number of optimized rules by analyzing frequent itemsets. The product usability is evaluated by applying those optimized association rules generated on feature related review sentences in the dictionary. Finally, capability evaluation is evaluated in Feature Fatigue (FF) analysis phase. By the determined measures of usability evaluation and capability evaluation, the process of feature fatigue analysis is performed to identify FF degree. This helps in alleviating the feature fatigue effectively.

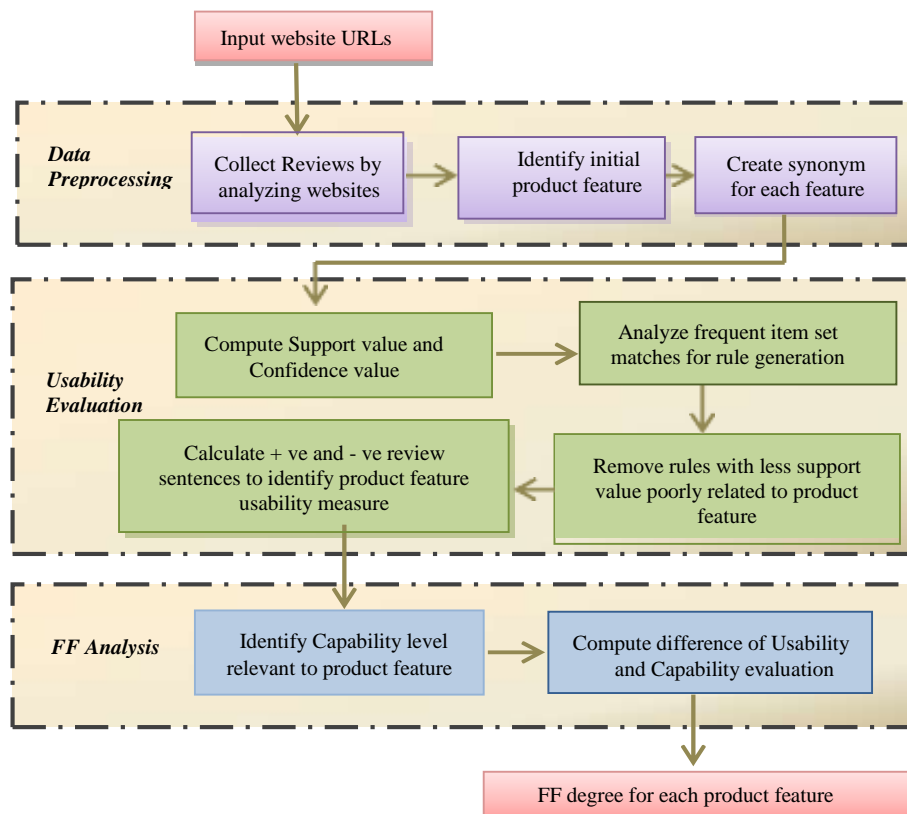The framework of the proposed methodology is shown in Figure 1.

Figure 1. Framework of Proposed DFARM Method

4. Data Preprocessing

In this preprocessing phase, the collected raw reviews are converted into review sentences. And using those preprocessed review sentences the synonym dictionary is created. The following sections explain the process of LDA and Lexicon Algorithm in generating the synonym dictionary. In this phase collection of reviews, preprocessing procedure and creation of synonym dictionary are performed.

4.1. Collection of Reviews

The process of collecting reviews is started by collecting the raw reviews of the customers' opinion about the product and its features from various websites using the web crawler tool. The web crawler tool is used to analyze contents in web pages and provides product reviews as output. Those collected raw reviews are stored in review collection database, then preprocessed and converted in to review the sentences. The process of collecting product reviews is demonstrated in the following Figure 2.
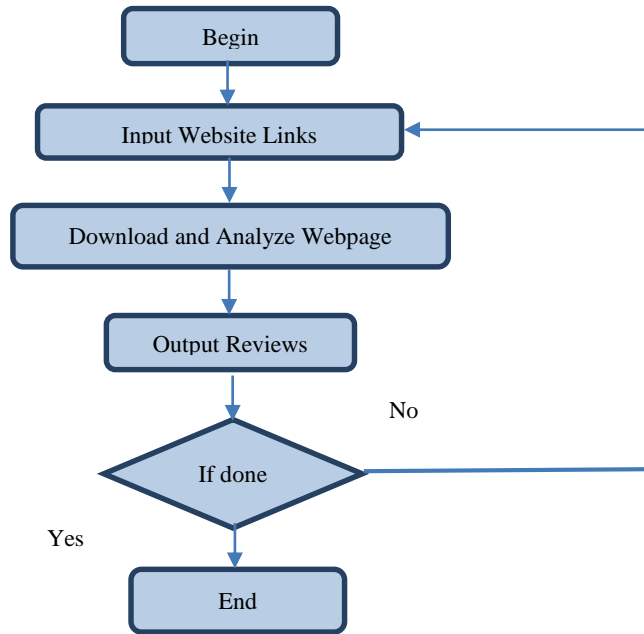

Figure 2. Review Collection Process using a Web Crawler Tool

4.2. Preprocessing Procedure

The customers provide the opinions in their own form of words in online about the experience they had on the product and its features. In the reviews posted many words used by the customers may denote to a single and same feature. Identifying the synonyms from such feature is a very difficult process. To analyze and identify such cases Natural Language Processing (NLP) is applied for Part of Speech (POS) tagging on the collected raw reviews. Part-of-speech (POS) tagging is a basic requirement of NLP systems. The process of POS tagging is performed on each review text before considering by LDA model. Part-of-speech tagging (POS tagging) is the method of reviewing a text and parse each word as matching to a specific POS, based on its description such as noun, verb, etc. The POS tagging identifies the initial product feature set of the extracted nouns. POS tagging process is performed on a Sequence of words, W by assigning a sequence of tags, T and computed by identifying the tags which have the maximum frequency in the sequence of words. The process is technically using following equations 1-4.

$$P(T|W) = P(W|T) \ P(T) \ / \ P(W) = \alpha \ P(W|T)P(T) \tag{1}$$

$$P(T) = P(t_1) \ P(t_2/t_1) \ P(t_3/t_1,t_2) \ P(t_3/t_1,t_2,t_3) \ldots . \ P(t_n/t_1,t2\ldots t_{n-1}) \tag{2}$$

$$P(W|T) = P(w_1/t_1) \ P(w_2/t_2)\ldots .P(w_n/t_n) \tag{3}$$

$$P(T) \ P(W|T) \approx P(t_1) \ P(t_2/t_1) \ \ldots \ldots . \ P(t_n/t_{n-1}) \ P(w_1/t_1) \ P(w_2/t_2)\ldots .P(w_n/t_n) \tag{4}$$

These extracted features are stored in review database and then processed by the LDA

model to generate the final product feature sets. The synonym dictionary is created by processing the extracted features using LDA and Lexicon algorithm.

4.3. Creation of Synonym Dictionary

In this process, for extracting the features from the collected reviews, integrated LDA and lexicon synonym is applied. The process of synonym dictionary is demonstrated in Figure 3.
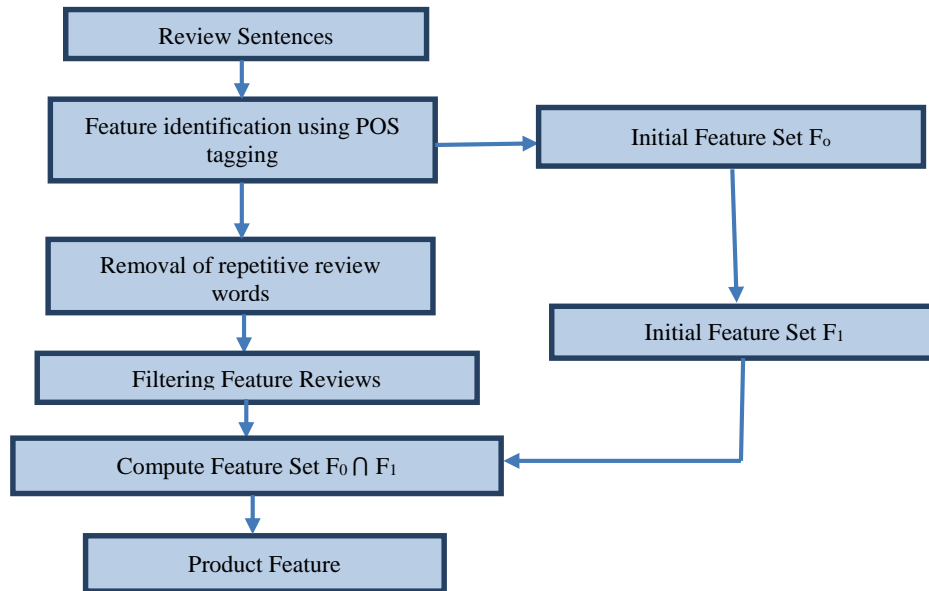

Figure 3. Process of Synonym Dictionary Creation

Table 1 demonstrates the process of LDA and Lexicon Synonym in creating the synonym dictionary.

Table 1. Pseudo Code of LDA with Lexicon Synonym Dictionary

D_i: Document in review corpus D
μ_i: Topic distribution of D_i
Dt: Dirichlet distribution
α, β: Parameters of Dirichlet prior
ϑ_k: Word distribution of topic k
$W_{i,j}$: word
$t_{i,j}$: topic of j_{th} word in D_i
Begin
  For each D_i:
    Select $\mu_i \sim Dt(\alpha)$
    Select $\vartheta_k \sim Dt(\beta)$
  End for
  For each word W_{ij}:
    Select topic $t_{ij} \sim Multinomial(\mu_i)$
    Select a specific word
  $W_{ij} \sim Multinomial\left(\vartheta_{t_{i,j}}\right)$
  End for
  For each word W_i in F_1
  For each syn or near-syn in synonym lexicon
    Assign $D = syn_i$ if $syn_i \nexists D$
  End for
  Set $F_2 = F_1 \cup D$
End

In this phase, the synonym dictionary creation is performed with the help of LDA and Lexicon algorithm. The following section describes the product usability evaluation phase of the proposed contribution.

5. Product Usability Evaluation

In this phase, the review sentences are analyzed to generate rules for evaluating the product usability. Initially, the frequent itemset is identified by calculating the support and confidence values of each feature. The obtained frequent itemsets are processed by improved FP-Growth frequent itemset algorithm for generating the association rules. And by applying the DSLC -FOA algorithm rule set reduction is performed to prune the generated rules. Finally, by matching the pruned rules set, product usability is evaluated. Frequent itemset, generating Association Rules, Rule Set Reduction, and usability evaluation processes are performed and explained in the following sections.

5.1. Frequent Itemset

For generating the rules by analyzing review sentences the association rule mining is applied. As an association rule mining is the most effective technique in finding the frequent pattern and associations among the information sources, in this work the rule mining is applied to identify the review sentences related to usability features. The problem statement for mining the association rule is, where ls refers to the utmost as shown in equation 5 and 6.

$$ls = \{ls_1, ls_2, ls_3, ls_4 \dots ls_{n,}\} \tag{5}$$

And the transaction set as Trans

$$Trans = \{T_1, T_2, T_3, T_4 \dots T_{n,}\} \tag{6}$$

In the process each transaction set, *Trans* contains the item of an itemset, *ls*. The form of an association rule is $p \not{\emptyset} q$, where p and q are the items of *ls*, $p \cap ls$, $q \cap ls$ and $p \cap q$. So, when p is contained in the transaction set, and then q will also rely on. An itemset is confirmed as a frequent itemset when its support value is greater than or equal to its threshold value. In this work Memory, RAM, Battery, Processor, etc. are some of the itemsets and clear, better, simple, good, nice, worst, etc. are the items. In the process of identifying association rules, high support items are applied. Based on the transaction percentage the support for the rule is stated and used in transaction *T*. The support of a rule is computed using the following equation 7.

$$support(p \rightarrow q) = \frac{p \cup q}{N} \tag{7}$$

In the above-mentioned equation, $p \cup q$ refers to the total number of transactions of all items of the rule and *N* represents the total transactions. This computation provides the value of relative support. The confidence value is stated by computing its transaction percentage with p which contains q as shown in below equation 8.

$$C(p \Longrightarrow q) = \frac{support(p \rightarrow q)}{support(p)} \tag{8}$$

The confidence value computation is a more important measure which views all transactions that contain certain item defined by the rule. The measures computed on the reviews and identified itemsets are processed by improved FP-Growth Frequent Itemset algorithm for generating the rules in the next process.

5.2. Generating Association Rules

For mining frequent itemset and learning of association rules, improved FP-Growth

Frequent Itemset algorithm is applied for effective performance. This process is performed by identifying each individual frequent itemset from the database and analyzes the total number of transactions in the database. Based on the matches between identified frequent itemsets and general trends of the database, association rules are determined. As the FP-Growth Frequent Itemset algorithm processes the analysis repeatedly for identifying the frequent itemset, it has the limitation to perform in many transactions.

In FP-Growth Frequent Itemset the scanning process of the database is repeated for many times to identify the candidate itemsets. This takes more execution time. To overcome this limitation by reducing the execution time in identifying the candidate itemsets, an Improved FP-Growth Frequent Itemset algorithm is applied for processing the itemsets in the review database.

The improved FP-Growth Frequent Itemset algorithm decreases the total number of candidate items in the candidate itemset, C_j, whereas, in FP-Growth Frequent Itemset algorithm, C_j is verified with the support value. If the itemsets are less than the support value, then it is pruned and the itemset f_i is produced which relates to itself and lead to C. Table 2 shows improved FP-Growth Frequent Itemset algorithm.

Table2. Pseudo Cof Improved FP-Growth Frequent Itemset Algorithm

S_i: Set of sentences

f_i : Frequent Item set

C_j: Candidates generated from f_i

T: Database

Min_sup: Minimum support

Begin

   $f_1 = Frequent_1 - itemset(d)$

   for $(j = 2 ; f_{i-1} \neq \emptyset ; + +)$

       prune $I(f_i)$

       $C_j = apriori\_gen(f_i; Min\_sup)$

   for all sentences $s \in d$

       find the subset to all $C = subset(C_k, s)$

   for each candidate $c \in C_c$

          $c.count + +$

     $f_i = \{c \in C_j | c.count \geq \min\_sup\}$

   return $U_i f_i$

end

In the improved FP-Growth Frequent Itemset algorithm, before generating the candidate itemsets C_j the pruning method counts the times on all items occurred in f_i and deletes the itemsets which are less than supportive value. By this improvisation process the number of

connecting itemsets will be reduced, hence the number of candidate items is also reduced. In the proposed approach, improved FP-Growth Frequent algorithm is applied to obtain the frequent itemset of customer review sentences. A set of sentences $S_i=(w_1,w_2... w_n)$, where w is the words in the S. The frequent set of S_i is obtained by applying Improved FP-Growth procedure. As a result of applying improved FP-Growth Frequent Itemset algorithm, association rules are generated by evaluating the support value of frequent itemsets identified from product feature review sentences.

5.3. Rule Set Reduction

The number of rules generated by improved FP-Growth Frequent Itemset algorithm is reduced by applying DSLC-FOA algorithm. Association rules obtained by improved FP-Growth Frequent Itemset algorithm provided as input for DSLC-FOA technique to identify optimal rules. DSLC-FOA optimization technique analyses the rules and relates to each product feature, based on the support value it removes the rules which has little support values and poorly related to the product feature compared to other rules. This process of removing less concerned rules provides a list of association rules which are more optimized.

In this work, the concept of fruit fly optimization is applied to obtain the product feature set from the synonym dictionary. In the process, the parameters of the synonym dictionary are considered as initial values referred to as Init X_{axis} and Init Y_{axis} for computing the association rules to be pruned. Those pruned rules are verified with the support values towards the features and then optimized by removing certain rules with minimum support. The rules which remain are optimized rules considered as input for processing product usability evaluation in the following section. The processing DSLC-FOA algorithm is represented in the following Table 3.

Table 3. Pseudo Code of DSLC-FOA Algorithm

Fsl: Fruit fly swarm location
Rv: Random value, Dt: Distance to an origin
S: Approximate value of Smell concentration
$Smell_i$: Smell concentration value
Fitness_fn: smell concentration judge function
Begin

$$X_i = X_{axis} + Rv$$
$$Y_i = Y_{axis} + Rv$$

do
if (food position= unknown)
find Dt and S

$$Dt_i = \sqrt{X_i^2 + Y_i^2}$$
$$S_i = \frac{1}{Dt_i}$$

endif
Substitute S into fitness_fn

$$Smell_i = fitness\_fn(S_i)$$
$$While\ (Smell_{i-1} > Smell_i)$$
$$Assign\ bestsmell = max(Smell)$$
$$X_{axis} = X(bestindex)$$
$$Y_{axis} = Y(bestindex)$$

End

5.4. Usability Evaluation

After the process of rule mining is performed, the optimal rules are included in the new review sentence. This process helps in selecting the rule which matches with the sentences. Based on the confidence value and the support value the classifier identifies the rule that matches with the sentence. The manufacturers can identify and focus on the features with a number of negative usability sentences. But for effective processing, for each product feature, usability level should be identified which can be evaluated using equation 9 as in below.

$$Un = \alpha(n_N) - n_p \tag{9}$$

Where n_N represents the number of negative review sentences, n_p represents the numbers positive review sentences and α is the importance level of negative impact related to positive impact. As the measures of product usability measure are displayed in the following Table 4.

Table 4. Product Usability Evaluation Measures

Measure	Description
1	Strong positive impact
2	Somewhat strong positive impact
3	Somewhat weak positive impact
4	Weak positive impact
5	Not apparent impact
6	Weak negative impact
7	Somewhat weak negative impact
8	Somewhat strong negative impact
9	Strong negative impact

The process of product usability evaluation is performed as discussed in the above section. And based on customers impact levels product feature usability measure is identified for each feature. These usability measures identified are processed to compute FF degree in FF analysis in the following section.

6. FF Analysis

The customers seek for the number of features for the products they buy; this factor may result in dissatisfactory when the feature doesn't fulfill their expectations. This product usability problem is called Feature Fatigue (FF). The focus of this research work is to solve this problem by alleviating FF by analyzing the product usability and capability evaluation measures.

6.1. Capability Evaluation

The capability evaluation is also performed as like the measures computed for product usability evaluation. The classified review sentences based on association rules generated are considered on their capability, relevance to the product feature. Based on the impact of the relevant review sentences in the synonym dictionary capability level is measured. The capability measures are obtained by processing the product capability through analyzing the customer reviews and displayed in the following Table 5. These obtained capability measures are to be provided as input with the usability measure obtained in earlier processing to compute FF Degree in the following section.

Table 5. Product Capability Evaluation Measures

Measure	Description
9	Extremely attractive
8	Very attractive
7	Attractive
6	Somewhat attractive
5	Neutral
4	Somewhat not attractive
3	Not attractive
2	Not attractive at all
1	Extremely not attractive

6.2. FF Degree

The product capability is evaluated for processing FF analysis in the next step. The obtained measures of product usability and product capability are applied to identify the FF degree. The computation of FF degree is processed using the equation 10.

$$FF\ Degree = UE - CE \tag{10}$$

In the above formula, the terms *UE* and *CE* represents the normalized values of usability and capability measures obtained by computing the equations 11 and 12.

$$UE = \frac{FUE - FUE_{Min}}{FUE_{Max} - FUE_{Min}} \tag{11}$$

$$CE = \frac{FCE - FCE_{Min}}{FCE_{Max} - FCE_{Min}} \tag{12}$$

The variable *FUE* represents the Feature Usability Evaluation. *FUE* is obtained by evaluating measures obtained in Table 4. In similar, *FCE* represents the Feature Capability Evaluation which is calculated using the measurements obtained in Table 5. This evaluation process of identifying the value of FF Degree for each feature by applying usability and capability measures provides an analysis of Feature Fatigue. Moreover, it helps manufacturers in alleviating the Feature Fatigue of a product.

7. Experimental Setup and Results

In experimentation, the collected raw reviews are converted in to review sentences by preprocessing method and those identified review sentences related to the product features are collected to form a synonym dictionary. By analyzing the review sentences in the dictionary, the association rules are generated, and the numbered rules are reduced by the optimization process. Using those optimized minimum number of association rule product usability and capability measures are evaluated. And the measures obtained are analyzed to find FF degree. The proposed method is implemented using Java. For validation the reviews of the product, Samsung Laptops are collected from an online using web crawler. These raw reviews are the input of this proposed work. To perform the proposed work, 2000 sentences are collected from the web. All those collected sentences are categorized into three sets of sentences as follows.

- A positive attitude toward Usability *PU*

- The negative attitude on Usability *NU*

- Not on Usability *NT*

Upon processing 260 PUs, 228 NUs and 1312 NTs are classified. In data preprocessing phase, removal of stop words and stemming is performed to extract words that represent

the product feature. In total there are 50,000 words in the reviews collected. On processing the preprocessing phase 30,212 words are removed Using LDA and Lexicon algorithm synonym dictionary is created. The generated dictionary form is shown in Table 6 below.

Table 6. Generated Synonym Dictionary

Feature	Synonym
Processor	CPU, machine, company, prepares
Speed	move quickly, hurry, race, run, sprint, dash
Cache	hoard, store, stockpile, stock, supply, collection
Memory	recollection, remembrance, reminiscence, evocation
RAM	force, thrust, plunge, stab, push, sink, dig, stick, cram
Display Features	exhibit, show, put on the show, put on view, layout, set out

Using the preprocessed collection of reviews related to the features in the form synonymy dictionary, evaluation of product usability is processed by applying the association rules generated and usability measure is obtained as in Table 7.

Table 7. Product Feature Usability Measure by DFARM Method

Features	Measure	Description
Processor	1	Strong positive impact
Speed	2	Somewhat strong positive impact
Cache	2	Somewhat strong positive impact
RAM	3	Somewhat weak positive impact
Memory	5	Not apparent impact
Screen size	7	Somewhat weak negative impact

Similarly, as the product usability evaluation is performed, product capability evaluation is also processed by using the association rule generated by DFARM to analyze the review sentences in a synonym dictionary. Table 8 represents the obtained measure by evaluating the product capability.

Table 8. Result of Capability Evaluation Measure of DFARM Method

Features	Measure	Description
Processor	7	Attractive
Speed	2	Not attractive at all
Speed	2	Not attractive at all
Screen size	4	Somewhat not attractive
Cache	2	Not attractive at all
RAM	6	Somewhat attractive
Memory	7	Attractive
Inbuilt HDD	3	Not attractive
Optical Drive	6	Somewhat attractive
Chipset	9	Extremely attractive

As the measures of product usability and product capability are obtained, feature fatigue analysis is performed by computing the Feature Fatigue Degree (FFD) using those two measures obtained from previous steps. For analyzing Feature Fatigue, the value of FF degree is identified by computing the difference between UE and CE. In this evaluation process, values of FUE and FCE are identified by using the measures obtained in Table 7 and Table 8. To calculate UN, negative review sentences n_N and positive review sentences

n_p are used with the α value of 2 are applied and processed. The result of FF analysis computed with results of usability and capability evaluation results is shown in the following Table 9. The parametric result obtained on evaluating the usability classification and is displayed in Table 10.

Table 9. Result of FF Degree Computation

Feature	*FUE*	*FCE*	*UE*	*CE*	*FF Degree*
Processor	1	8.5	0.00	0.94	-0.94
Speed	2	7.25	0.00	0.78	-0.78
Cache	2	6.25	0.00	0.66	-0.66
RAM	3	7.50	0.25	0.81	-0.56
Memory	5	2.50	0.50	0.19	0.31
Screen size	7	6.25	0.75	0.66	0.09
Inbuilt HDD	7	4.75	0.75	0.47	0.28
Optical Drive	9	2.75	1.00	0.27	0.73
Chipset	9	2.50	1.00	0.19	0.81

Table 10. Performance of Product Feature Usability Evaluation for DFARM

Performance Metrics	DFARM Method
Precision (%)	96
Recall (%)	95
F-Measure (%)	99
Accuracy (%)	99

The results obtained after the experimentation of product usability and FF analysis provides better accuracy as discussed in the above sections. The test analysis report is generated on true positive, true negative, false positive and false negative rate which is used for providing an accurate result in product usability. The values obtained using DFARM method is shown in Figure 4.
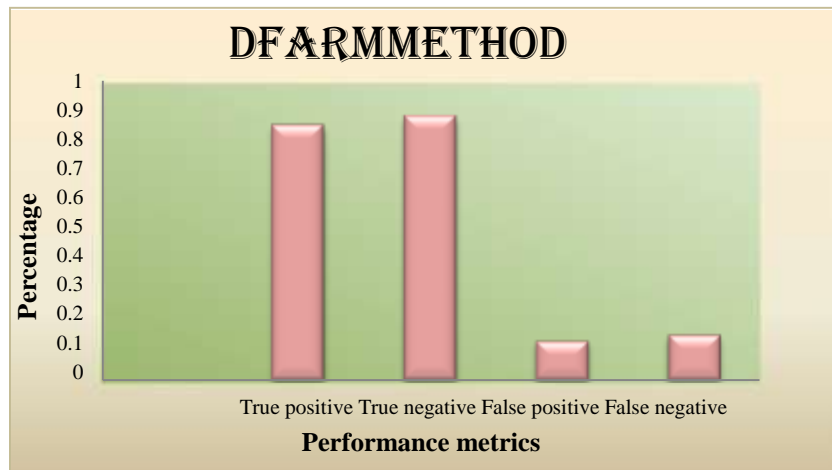

Figure 4. The Result of Test Analysis Report for DFARM

The DFARM method obtains the result in 82 seconds of execution time with 52 Mbps memory utilization.

8. Conclusion

In this paper, the proposed DFARM method with three phases evaluates Product Usability and the capability to analyze Feature Fatigue. The customer reviews are collected through web crawler and preprocessed by applying NLP with POS Tagging. And using LDA with Lexicon Synonym algorithm the synonym dictionary is formed. Then the novel approach, DFARM method is applied to evaluate the review sentences by generating a minimum number of optimized association rules. In the final phase, feature fatigue analysis is performed to identify FF degree. Upon implementing the three phases of experimentation, the results obtained provide better precision value with 96%, Recall value of 95% and by evaluating the F-Measure the obtained measure is about 99% which resulted in the usability classifier with 99% of accuracy. This shows that the proposed contribution helps manufacturers to analyze the usability of product features and helps in making decisions to alleviate Feature Fatigue in product designing.

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